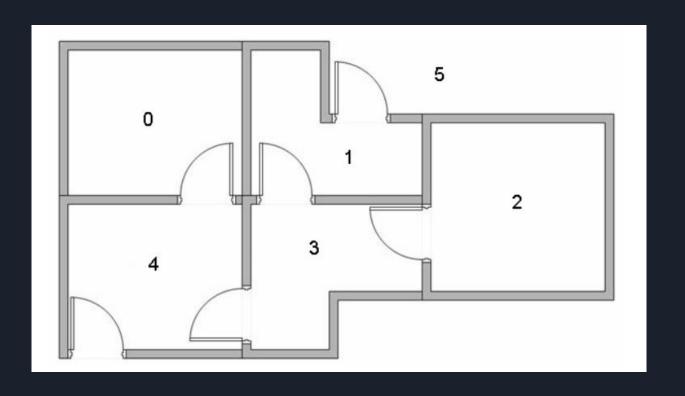
# Q-Learning to solve a maze problem

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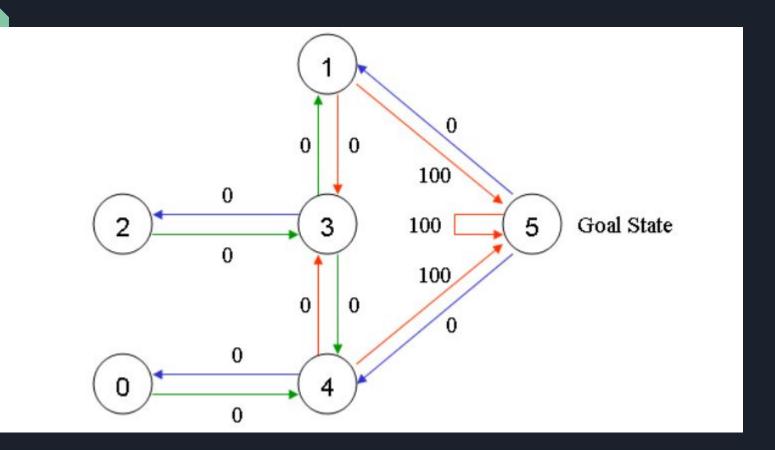
# Outline

- 1. Introduction
- 2. Model Proposal
- 3. Results
- 4. Conclusion

# Introduction: Previous Work



## Introduction: Previous Work



# Model Proposal

- States: equal to the dimension of the maze, m x n.
- Actions: Left, Top, Right, Down



## Q-matrix

Actions:4

$$Q = \begin{bmatrix} -500 & -500 & 0 & -500 \\ 0 & -500 & 0 & -500 \\ \dots & \dots & \dots & \dots \\ -500 & 0 & 0 & -500 \\ 0 & 0 & -500 & -500 \end{bmatrix}$$

States:  $n^*m = 20^*20 = 400$ 

#### R-matrix

Actions:4

$$R = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & 100 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

States:

n\*m = 20\*20 = 400

We just give a reward of 100 when ant agent performs an action which moving it to the final position.

## Episodes and Hyperparameters

An episode is defined by a number of iteration: 200

Gamma: it is used to the rule of learning in Q-learning.

• Epsilon: it is used to defined the influences of exploration over the exploitation techniques.

### Results

Three different training with 400 states and 4 possible actions:





Total episodes: 21 Time: 8.24 minutes

Labyrinth completed: 96.75%

Total episodes: 23 Time: 10.24 minutes

Labyrinth completed: 98.5%

Total episodes: 24 Time: 10.42 minutes

Labyrinth completed: 96.75%

# Comparison of different training.



# Results

#### Training Time Average:

	The time that the agent takes to training on the Labyrinth				
	Time with 3 different training (seconds)			Average	
Dimension	1st	2nd	3nd		
20x20	493.8	614.4	614.4	574.2	

574.2 seconds = 9.57 minutes

# Results

#### Training Time Average:

	The time that the agent takes to training on the Labyrinth				
	Time with 3 different training (seconds)			Average	
Dimension	1st	2nd	3nd	VV	
10x10	306	288	330	308	

308 seconds = 5.13 minutes

#### Conclusiones

• **Q-learning** provides **agents** with the capability of **learning** to act **optimally** figuring out the maze solution.

• States(400) and actions(4) determine how this learning process is achieved.

### Conclusiones

• Q-learning **optimization** is done through **rewards** received (R matrix).

Q-learning Maze implementation demonstrate to be efficient.

#### Conclusiones

- A minimum of 96% of the labyrinth completed explored by the agent in 10 minutes.
- The time required to train the algorithm with respect to the maze dimension is linear.
- If the dimension of the labyrinth decreases, the agent takes less time to train.

#### THANK YOU

Git Hub Repository: <a href="https://github.com/ZosoV/QLearningMazeSolving.git">https://github.com/ZosoV/QLearningMazeSolving.git</a>

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